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REVIEW ON CONTENT BASED IMAGE RETRIEVAL SYSTEM

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Abstract: Content Based Image retrieval (CBIR) has been an active research area since past few years. In this thesis we have discussed the three main areas of CBIR which are feature extraction, indexing and the retrieval technique. We have also discussed briefly some of the commercial systems available in the market and apart from that some related work in this field is also discussed. Content based image retrieval has found its application in many areas like government, academic and hospitals. This paper proposed technique retrieves similar images in stages. The images are first retrieved based on their color feature similarity. The relevance of the retrieved images is then further improved by matching their texture and shape features respectively. Generally in CBIR we compare query image feature vector with all other images in the database. This decreases the accuracy of the system as the search encompasses the whole database which contains a wide variety of images. The proposed system in this paper has three layers feed forward architecture where each stage output is the input for next stage. Proposed approach also reduces the problem of high dimensionality of feature vector because at each stage only a part of the feature vector representing the desired feature need to be compared thereby resulting in reduction of computational overhead of the overall system. Retrieval in stages also reduces the semantic gap. Advantages of global and region features are also combined to achieve better retrieval accuracy. Experimental results have shown that the proposed system can improve the retrieval accuracy in terms of precision values.

I. INTRODUCTION

Interest in the potential of digital images has increased enormously over the last few years, fuelled at least in part by the rapid growth of imaging on the World-Wide Web. Users in many professional fields are exploiting the opportunities offered by the ability to access and manipulate remotely-stored images in all kinds of new and exciting ways. However, they are also discovering that the process of locating a desired image in a large and varied collection can be a source of considerable frustration. The problems of image retrieval are becoming widely recognized, and the search for solutions an increasingly active area for research and development [1]. Problems with traditional methods of image indexing have led to the rise of interest in techniques for retrieving images on the basis of automatically-derived features such as color, texture and shape – a technology now generally referred to as Content-Based Image Retrieval (CBIR). After a decade of intensive research, CBIR technology is now beginning to move out of the laboratory and into the marketplace, in the form of commercial products. However, the technology still lacks maturity, and is not yet being used on a significant scale. In the absence of hard evidence on the effectiveness of CBIR techniques in practice, opinion is still sharply divided about their usefulness in handling real-life queries in large and diverse image collections [2].

Problem Statement

There is a rapid increase of the size of digital image collections in recent years. Every day, both military and civilian equipment generates tera-bytes of images. Huge amount of information is out there. However, we cannot access to or make use of the information unless it is organized so as to allow efficient browsing, searching and retrieval. Image Retrieval has been a very active research area since the 1970,s. These two research communities study Image Retrieval from different angles, one being text-based and the other visual-based. The text-based Image Retrieval can be traced back to the late 1970,s. A very popular framework of Image Retrieval then was to first annotate the images by text and then use text-based Database Management Systems (DBMS) to perform Image Retrieval. Many advances have been made along this research direction. However, there exist two major difficulties, especially when the size of image collections is large (tens or hundreds of thousands).

Applications

A wide range of possible applications for CBIR technology has been identified. Potentially fruitful areas include [3]:

- Crime prevention
- The military
- Intellectual property
- Journalism and advertising
- Medical diagnosis
- Geographical information and remote sensing systems
- Education and training
- Home entertainment
- Web searching.

Closer examination of many of these areas reveals that, while research groups are developing prototype systems, and practitioners are experimenting with the technology, few examples of fully-operational CBIR systems can yet be found.

Feature extraction

Feature extraction is the basis of content-based Image Retrieval. In broad sense, features may include both text-based features (keywords, annotations, etc.) and visual features. However, since there already exist rich literatures on text-based feature extraction in the DBMS and Information Retrieval research communities, we will confine ourselves in the techniques of visual feature extraction. Within the visual feature scope, the features can be further classified as general features and domain specific features. The former include color, texture and shape features while the latter is application dependent and may include, for example, human faces and finger prints. Because of perception subjectivity, there does not exist a single best presentation for a given feature. As we will see soon, for any given feature, there exist multiple representations which characterize the feature from different perspectives [4].

Color

Color feature is one of the most widely used visual features in Image Retrieval. It is relatively robust to background complication and independent of image size and orientation. In Image Retrieval, Color Histogram is the most commonly used color feature representation. Statistically, it denotes the joint probability of the intensities of the three color channels. Furthermore, considering that most Color Histograms are very sparse and thus sensitive to noise. Besides Color Histogram, several other color feature representations have been applied in Image Retrieval, including Color Moments and Color Sets. To overcome the quantization effects as in Color Histogram. The mathematical foundation of this approach is that any color distribution can be characterized by its moments. Furthermore, since most of the information is concentrated in the low-order moments, only the first moment (mean), and the second and third central moments (variance and skewness) were extracted as the color feature representation. Weighted Euclidean distance was used to calculate the color similarity, to facilitate fast search over large-scale image collections. They first transformed the (R, G, B) color space into a perceptually uniform space, such as HSV, and then quantized the transformed color space into M bins. A Color Set is defined as a selection of the colors from the quantized color space. Because Color Set feature vectors were binary, a binary search tree was constructed to allow fast search.

Texture

Texture refers to the visual patterns that have properties of homogeneity that do not result from the presence of only a single color or intensity. It is an innate property of virtually all surfaces, including clouds, trees, bricks, hair, fabric, etc. It contains important information about the structural arrangement of surfaces and their relationship to the surrounding environment. Because of its importance and usefulness in Pattern Recognition and Computer Vision, there existed rich research results in the past three decades. Now, it further finds its way in Image Retrieval. More and more research achievements are being added to it. It first constructed a co-occurrence matrix based on the orientation and distance between image pixels and then extracted meaningful statistics from the matrix as the texture representation. Many other researchers followed the same line and further proposed enhanced versions.

Shape

In Image Retrieval, depending on the applications, some require the shape representation to be invariant to translation, rotation, and scaling; while others do not. Obviously, if a representation satisfies the former requirement, it will satisfy the latter as well. Therefore, in the following we will focus on shape representations that are transformation invariant. In general, the shape representations can be divided into two categories, boundary-based and region-based. The main idea of Fourier Descriptor is to use the Fourier transformed boundary as the shape feature. To take into account the digitization noise in the image domain, Fourier Descriptor is both robust to noise and invariant to geometric transformations. The main idea of Moment Invariants is to use region-based moments, which are invariant to transformations, as the shape feature. Shape may be defined as the characteristic surface configuration of an object. It permits an object to be distinguished from its surroundings by its outline. Two main types of shape feature are commonly used – global features such as aspect ratio, circularity and moment invariants and local features such as sets of consecutive boundary segments.

High dimensional indexing

To make the content-based image retrieval truly scalable to large size image collections, efficient multi-dimensional indexing technique need to be explored. There are two main challenges in such an exploration for image retrieval:

High dimensionality

The dimensionality of the feature vector is normally of the order of 102

Non-Euclidean similarity measure

Since Euclidean measure may not effectively simulate human perception of a certain visual content, various other similarity measures, such as Histogram Intersection, Cosine, Correlation, etc., need to be supported. Towards solving these problems, one promising approach is to first perform dimension reduction and then use appropriate multi-dimensional indexing techniques, which are capable of supporting Non-Euclidean similarity measures.

II. PROPOSED WORK

Multistage CBIR is recently proposed in the year 2012 by Nishant Shrivastava and Vipin Tyagi. My main aim is to improve the efficiency of the algorithm by increasing the precision or recall of the proposed algorithm. The proposed method work on three layer feed forward architecture. Each layer narrow down the search range by filtering irrelevant images based on color, texture and shape features respectively. Retrieving images in this manner helps in reducing the semantic gap and to an extent eliminate the need of precise segmentation technique which has been a great hurdle in the field of image retrieval. This approach also reduces the problem of high dimensionality of the feature vector as at each stage only a part of the feature vector, representing the desired feature, need to be compared with the query image. Moreover both global and region features are combined to obtain better retrieval accuracy. Thus we are trying to modify the feature vector at each stage for better accuracy.

Haralick Texture Features

Robert Haralick described 13 statistics that can be calculated from the co-occurrence matrix with the intent of describing the texture of the image [14] we have calculated all the thirteen features from the matrix and compared it with the query image. They are as follows:

Angular second moment, contrast, correlation, sum of squares: variance, inverse difference moment, sum average, sum variance, sum entropy, entropy, difference variance, difference entropy, information measures of correlation, maximal correlation coefficient.

Gray Level Co-Occurrence Matrix (GLCM)

The GLCM is a tabulation of how often different combinations of pixel brightness values (grey levels) occur in an image. The GLCM described here is used for a series of "second order"

Texture calculations. First order texture measures are statistics calculated from the original image values, like variance, and do not consider pixel neighbor relationships. Second order measures consider the relationship between groups of two (usually neighboring) pixels in the original image. Third and higher order textures (considering the relationships among three or more pixels) are theoretically possible but not commonly implemented due to calculation time and interpretation difficulty.

Each pixel within the window becomes the reference pixel in turn, starting in the upper left corner and proceeding to the lower right. Pixels along the right edge have no right hand neighbor, so they are not used for this count.

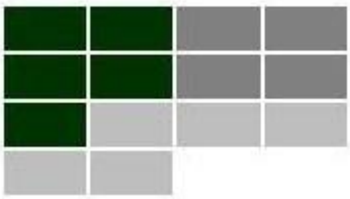

Figure 1 Example image for GLCM

Example shown in fig-1 here uses 1 pixel offset (a reference pixel and its immediate neighbor). If the window is large enough, using a larger offset is perfectly possible. There is no difference in calculation method. The sum of all the entries in the GLCM (i.e. the number of pixel combinations) will just be smaller for a given window size. Thus it can be derived as Twice in the test image the reference pixel is 0 and its eastern neighbor is also 0. Twice the reference pixel is 0 and its eastern neighbor is 1. Three times the reference pixel is 2 and its neighbor is also 2 etc.

Shape Features

The proposed algorithm considers the largest bounding box generated by the region growing algorithm and calculates the shape features we have included a new shape feature known as orientation. It is the angle (in degrees ranging from -90 to 90 degrees) between the x-axis and the major axis of the ellipse that has the same second-moments as the region. This property is supported only for 2-D input label matrices. This figure illustrates the axes and orientation of the ellipse. The left side of the figure shows an image region and its corresponding ellipse. The right side shows the same ellipse, with features indicated graphically:

- The solid blue lines are the axes.
- The red dots are the foci.

The orientation is the angle between the horizontal dotted line and the major axis.

Figure-2 Orientation property of the image

Region Growing Algorithm

Region growing is a simple region-based image segmentation method. It is also classified as a pixel-based image segmentation method since it involves the selection of initial seed points. This approach to segmentation examines neighboring pixels of initial “seed points” and determines whether the pixel neighbors should be added to the region. The first step in region growing is to select a set of seed points. Seed point selection is based on some user criterion (for example, pixels in a certain gray-level range, pixels evenly spaced on a grid, etc.). The initial region begins as the exact location of these seeds. The regions are then grown from these seed points to adjacent points depending on a region membership criterion. The criterion could be, for example, pixel intensity, gray level texture, or color. Since the regions are grown on the basis of the criterion, the image information itself is important. For example, if the criterion were a pixel intensity threshold value, knowledge of the histogram of the image would be of use, as one could use it to determine a suitable threshold value for the region membership criterion. There is a very simple example followed below. Here we use 4-connected neighborhood to grow from the seed points. We can also choose 8-connected neighborhood for our pixels adjacent relationship. And the criteria we make here is the same pixel value. That is, we keep examining the adjacent pixels of seed points. If they have the same intensity value with the seed points, we classify them into the seed points. It is an iterated process until there is no change in two successive iterative stages. Of course, we can make other criteria, but the main goal is to classify the similarity of the image into regions

Here figure-3 shows the query image of a lightening on which the region growing algorithm is applied and the criteria is that the pixel value should be less than the mean of the region. Thus by applying this algorithm we get two regions in figure-4, B1 and B2 here since B1 is the biggest region it has maximum weight age in the image it is our region of interest and the feature vectors will be calculated of that region.

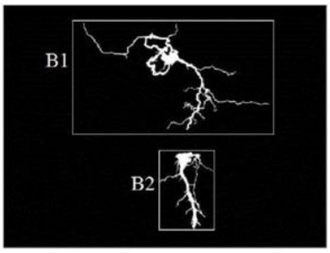

Figure-3 Query Image of Lightening
Figur-4 Finding Region of Interest

Color Features
The existing algorithm extracts three color features which can be further modified to extract two more features which are kurtosis and skewness.
Kurtosis - measures how peaked a distribution is and the lightness or heaviness of the tails of the distribution. In other words, how much of the distribution is actually located in the tails? A normal distribution has a kurtosis value of zero (0) and is said to be mesokurtic. A positive kurtosis value means that the tails are heavier than a normal distribution and the distribution is said to be leptokurtic (with a higher, more acute "peak").

III. IMPLEMENTATION AND RESULTS

A. Implementation Details
In order to implement the above algorithm, I've developed following files and one implementation file for shape feature extraction is still remaining.

- Multistage (This file is the main executable file which will be called for image retrieval)
- Color (This file extracts the color feature of each and every image and returns the feature vector back to multistage for comparison)
- Haralick.m (This file extracts the texture feature of each and every image and returns the feature vector back to multistage for comparison)
- Shape.m (This file extracts the shape feature of each and every image and returns the feature vector back to multistage for comparison)
- Pre.m (This file performs operation of converting image to cieLAB, denoising the image and then converting back to RGB and returns the RGB image back to multistage.m)

Following is an algorithm of the implementation work performed.

- Get query image.
- Perform preprocessing on the image.
- Extract color feature for the image obtained in step 2.
- Get all images in the database
- Repeat step 2 and 3 for all images in the database
- Calculate Euclidean distance from the result of step 5 with the features of the query image.
- If the Euclidean distance less than certain threshold store that image in an array list.
- Convert the image in step 2 to grayscale image.
- Calculate the texture feature of the image in step 8.
- Repeat step 7 and 8 for all images in the array list.
- Calculate Euclidean distance from the result of step 8 with the texture features of the query image.
- If the Euclidean distance less than certain threshold store that image in another array list.
- Apply averaging filter to the query image
- Convert the query image to Black and white image.
- Apply region growing algorithm to find the region of interest.
- Extract the region with maximum number of pixels.
- Calculate the shape feature of the image obtained in step 16.
- Repeat step 13 to 17 for all images in the array list.
- Calculate Euclidean distance from the result of step 18 with the shape features of the query image.
- If the Euclidean distance less than certain threshold. Display the result.

The output of the following algorithm is shown in figure 5:

Here the first image is the query image and the other eleven are the relevant images produced by the algorithm. In the proposed algorithm the threshold for color features is calculated as 13 and the threshold for texture feature is kept 5 and the threshold for the shape feature is kept 10. The results obtained by the proposed algorithm are satisfying and better than the existing algorithm.

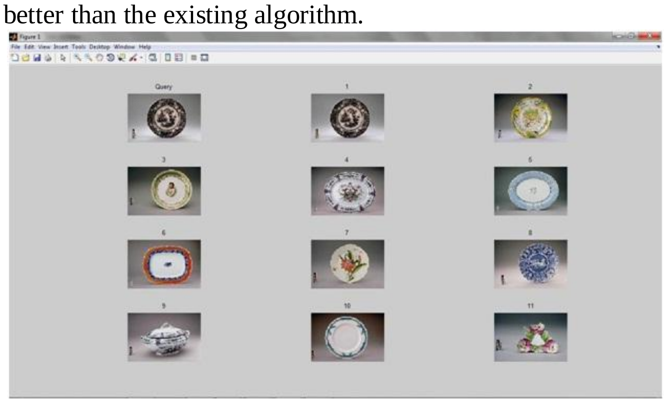

Figure 5 Output of the proposed algorithm

Comparison
Let us compare the proposed algorithm with the results obtained by the existing algorithm, for this we have implemented the existing algorithm, and the data set used is Corel database. The results obtained are quite satisfactory but not overwhelming. This section provides the experimental evaluation of proposed method vs. existing algorithm. A computer system having Intel core i5, 2.4 GHz processor and 4 GB RAM is used for conducting

experiments. This system has been implemented in MATLAB using coral database of 400 natural images.

Corel Dataset

The DCT research community has manually divided 10,800 images from the Corel Photo Gallery into 80 concept groups, e.g., autumn, aviation, bonsai, castle, cloud, dog, elephant, iceberg, primates, ship, stalactite, steam-engine, tiger, train, and waterfall. They reorganized the Corel Photo Gallery, because 1) many images with similar concepts were not in the same group and 2) some images with different semantic contents were in the same group in the original database. In the reorganized database, each group includes more than 100 images and the images in the group are category-homogeneous. These concept groups were used in the evaluation of the results of our algorithms.

Comparison

For comparison purpose we have used five random query images from four categories in the Corel data set and calculated the precision and recall values for each images for better understanding we have used chart to display the result. The first category is of doors we took five random images and applied to the existing algorithm as well as the proposed algorithm and compared the precision and recall values for both and we can see that the precision values of the proposed algorithm are quite good to the existing algorithm. But still the result shows fluctuation depending on the type of query image (Figure 6 and 7).

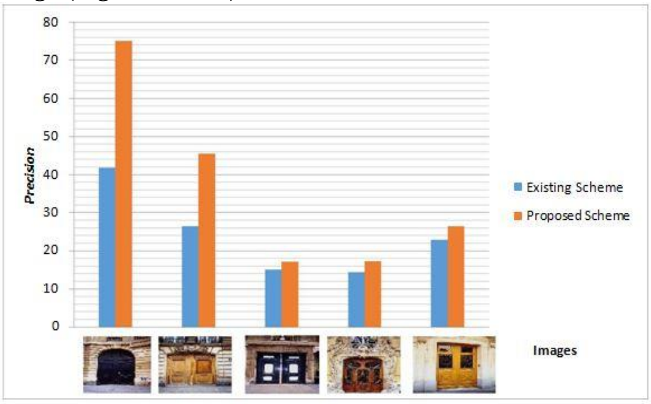

Figure 6 Precision values for category 1(Doors)

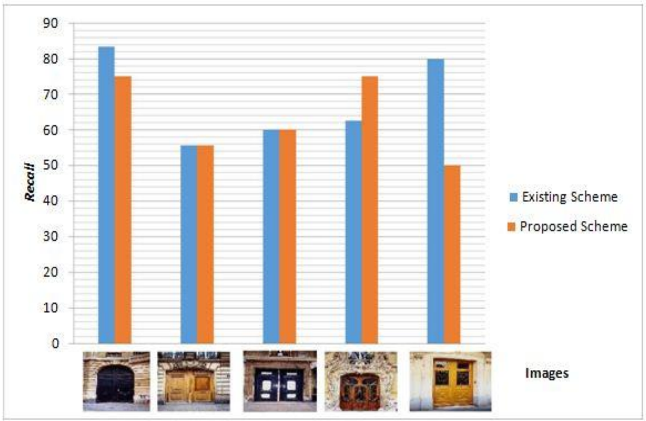

Figure7 Recall values for category 1(Doors)

The second category is of crockery and did the same process we took five random images and applied to the existing algorithm as well as the proposed algorithm and compared the precision and recall values for both and we can see that the precision values of the proposed algorithm and existing algorithm are similar except for some of the images. But still the result shows fluctuation depending on the type of query image (Figure 8 and 9).

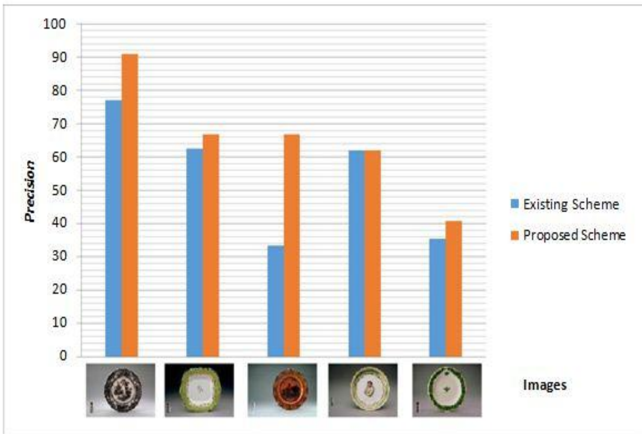

Figure 8 Precision values for category 2(Crockery)

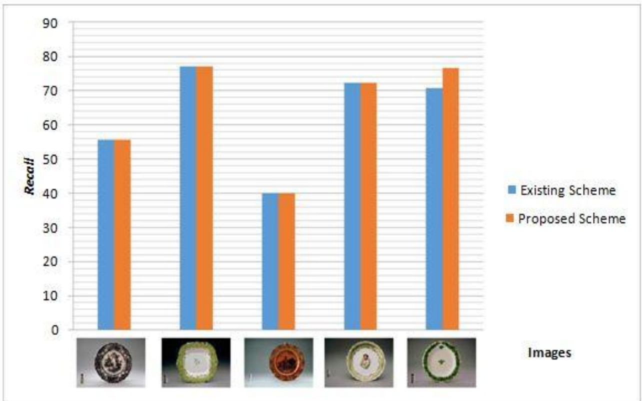

Figure9 Recall values for category 2(crockery)

The third category is of greenery based texture and did the same process but the outputs were satisfactory for both existing as well as proposed work. The precision values were as low as 30 percent for both the existing as well as the proposed work (Figure 10 and 11).

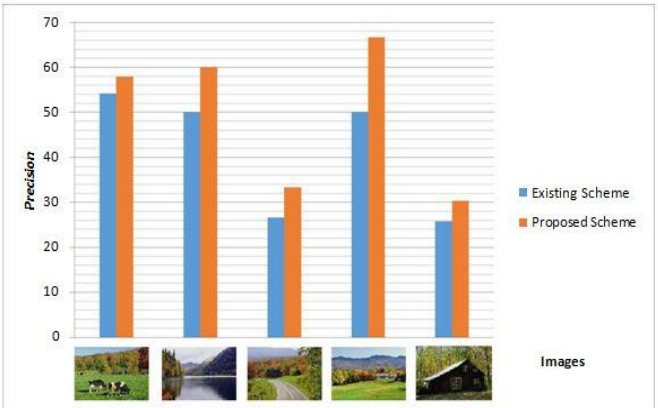

Figure 10 Precision values for category 3(Texture)

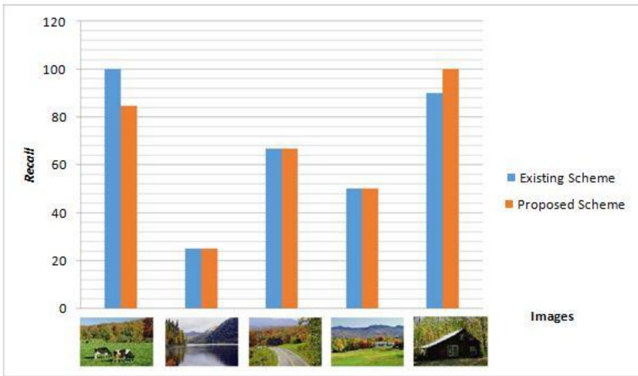

Figure 11 Recall values for category 3(Texture)

The fourth and the last category is of pet dogs and did the same process but the precision values for some query images were outstanding compared to the existing algorithm but for other query images it showed a great decline in the precision values but still it was better compared to the existing algorithm. But the recall values of the existing algorithm performed better than the proposed scheme (Figure 12 and 13).

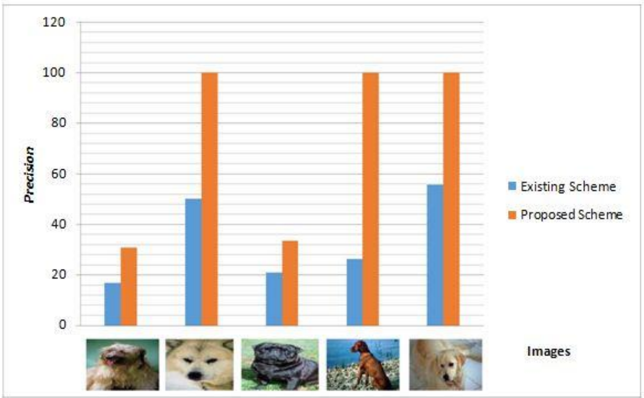

Figure 12 Precision values for category 4(Dogs)

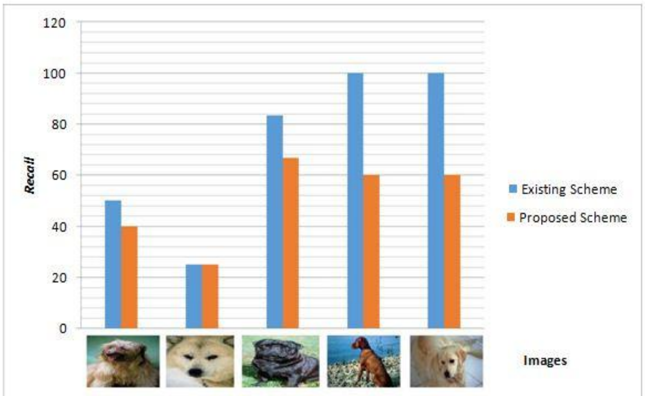

Figure 13 Recall values for category 4 (Dogs)

After comparing the precision and recall for the above four categories we have calculated the mean average precision and recall and can deduce that the proposed algorithm is far better than the existing algorithm in terms of precision values but slightly behind in terms of the existing algorithm but this results can be improved by adjusting the threshold values and modifying the feature vectors for suitable output (Figure 14 and 15).

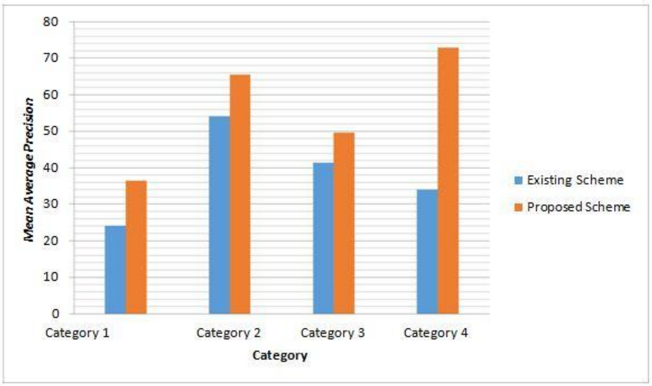

Figure 14 Comparison of mean average precision

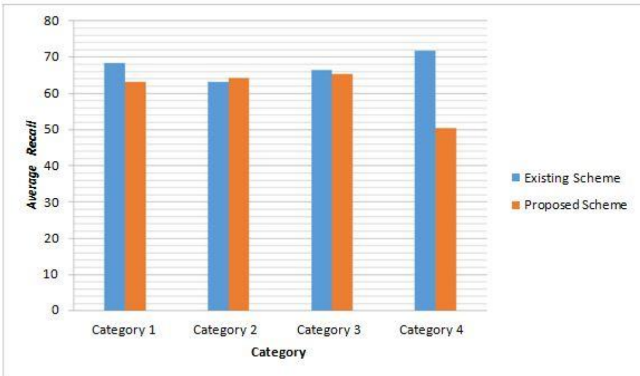

Figure 15 Comparison of mean average Recall

IV. CONCLUSION AND FUTURE WORK

This paper has enhanced an existing scheme in terms of precision values for retrieving images. The proposed method work on three layer feed forward architecture. Each layer narrow down the search range by filtering irrelevant images based on color, texture and shape features respectively. Moreover both global and region features are combined to obtain better retrieval accuracy. Experimental results obtained by our approach are encouraging for most of the query images. Since the precision values are higher compared to the existing algorithm it is good for the applications in which high precision is required and some techniques need to be implemented for increasing the recall percentage of the algorithm. This algorithm can be used as a base algorithm for some other algorithms like relevance feedback in image retrieval so that the recall factor does not affect significantly on the output of the image and serve as a good algorithm due its high precision value. It is possible to further improve the accuracy of the proposed system by employing different methods to extract features and modifying the feature vector.

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